# Hybrid Attention-Driven Deep Learning Framework for Cardiovascular Disease Classification

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**Abstract:** Cardiovascular diseases (CVDs) remain the leading cause of global mortality, underscoring the urgent need for early and accurate detection methods that surpass the limitations of conventional diagnostic approaches. This study proposes a Hybrid Attention-Driven Deep Learning Framework designed to enhance predictive accuracy by effectively leveraging heterogeneous clinical features. The dataset, obtained from the UCI repository, comprises 918 patient records containing demographic, physiological, and electrocardiographic attributes relevant to heart disease risk assessment. The proposed model integrates a dual-branch architecture one dedicated to processing numerical features through dense transformations and the other to encoding categorical variables using embeddings followed by a Multi-Head Attention Fusion Layer that captures complex inter-feature dependencies. Experimental results demonstrate that the proposed framework outperforms several traditional machine learning models, achieving a test accuracy of 0.897, an F1-score of 0.910, and an AUC of 0.930. These findings highlight the model's robustness, superior generalization capability, and strong potential for clinical decision support in early CVD diagnosis.
**Keywords**: Cardiovascular diseases; early-stage indicators; healthcare; machine learning; risk prediction

## Introduction

Every year, millions of people die from cardiovascular diseases (CVDs), which are the leading cause of death globally and have a significant economic and social impact. The prevalence of heart conditions has risen across all age groups due to sedentary lifestyles, elevated stress levels, and poor diets [1]. Even with advancements in diagnostic technology and therapeutic approaches, early diagnosis of CVDs remains a significant problem. The delicate or uncommon nature of early-stage symptoms, which frequently go unrecognized or are misinterpreted in clinics, is mostly to blame [2].

The rising incidence of heart disease in women, especially among young people, is one of the new problems in India. Women are currently dealing with an epidemic of cardiovascular risk factors, such as diabetes, hypertension, smoking, and obesity, despite historically not being considered to be as vulnerable as males [3]. The majority of women experience delayed diagnosis and bad outcomes, which are exacerbated by social standards and patients' and healthcare professionals' inability to identify symptoms. This highlights the need for data-driven, gender-sensitive diagnostic methods that can accurately identify CVDs' early warning indicators [4].

Traditional diagnostic methods typically rely on rule-based conclusions and subjective interpretation, both of which are prone to mistake and variability. By using artificial intelligence (AI) and machine learning

(ML) techniques that make it easier to analyze complicated, high-dimensional clinical data, these drawbacks can be overcome [5]. When combined with appropriate feature engineering techniques, machine learning algorithms have shown great promise in the medical field by facilitating automated predictions, identifying subtle patterns, and increasing diagnostic accuracy [6].

**Related work**

The recent developments in cardiovascular disease (CVD) prediction models illustrate the promise of machine learning (ML) and deep learning (DL) methods to enhance diagnostic performance and patient outcomes. Ogunpola et al. (2024) aimed at improving the detection of heart disease, specifically myocardial infarction, by comparing seven ML/DL models KNN, SVM, Logistic Regression, CNN, Gradient Boosting, XGBoost, and Random Forest on imbalanced datasets. Their research was a tremendous success, with XGBoost delivering 98.5% accuracy. A major strength of this study is its successful management of data imbalance and focus on algorithmic tuning. The main limitation of the study, though, is the absence of external validation, limiting its generalizability across wide-ranging populations.

In an independent endeavor, Drouard et al. (2024) investigated the prediction of CVD risk factors based on multi-omic datasets that included genomics, proteomics, and transcriptomics. Their approach compared six ML classifiers and state-of-the-art methods such as unsupervised/semi-supervised autoencoders and transfer learning. They established that multi-omic models outperformed single-omic models significantly, and model generalization was enhanced using transfer learning. Though these findings are encouraging, the models' complexity and dependence on omic data something not easily obtainable in routine clinical practice are a concern for large-scale deployment.

DeGroat et al. (2024) focused on CVD biomarker discovery to predict precision CVD with a hybrid approach that integrated statistical analysis with an ensemble of machine learning (ML) algorithms such as RF, SVM, XGBoost, and KNN. They identified and ranked transcriptomic biomarkers with a respectable 96% accuracy. Targeted diagnostics are enabled with the integration of ML for biomarker prioritization. However, the dependence of the model on data quality and interpretability issues related to ensemble approaches remain challenges for clinical translation.

While most research centers on technical accuracy, Cai et al. (2024) approached differently by critically examining the methodological flaws in existing ML models for predicting CVD. Their review has covered data quality, overfitting of the model, bias, and reproducibility. They suggested a systematic framework of best practices to improve the reliability and explainability of the model. Though their work is very valuable in informing the development of future studies, the lack of empirical testing restricts its direct real-world application.

For enhancing the early detection of CVD, an ensemble ML model was proposed by Korial et al. (2024), based on voting among Naïve Bayes, Random Forest, Logistic Regression, and KNN, coupled with chi-square feature selection. Predictive accuracy was enhanced to 92.11% and computational needs were reduced by half. Their dataset, however, consisted of just 303 samples, limiting the model's scalability and subjecting it to possibilities of overfitting and lack of generalizability.

Yet another innovative work is presented by Alghamdi et al. (2024), which designed a hybrid ML system combining an arithmetic optimization algorithm as a feature selector and an MLP as a classifier. The pipeline produced an accuracy of 88.89% and had a very robust preprocessing structure. Even though the system performed well with data, it suffered from imbalanced data and was compared only with conventional classifiers, so it was not fully evaluated from a complete set of recent models.

Moreno-Sánchez et al. (2024) provided a structured review of ML and DL techniques used to diagnose and predict CVD from ECG-based approaches. The research centered on data modalities, principles of trustworthy AI, and ethical issues like bias, explainability, and transparency. Their review offered an integrated perspective of the prevailing trends and challenges for ECG-based diagnostics. Nevertheless, its reliance on secondary data and absence of novel experimentation limit its impact on algorithm design and real-world deployment.

**Table 1: Highlighting advancements, methodologies, advantages, and limitations of AI-driven approaches in CVD detection and management.**

| Reference | Objective | Methodology | Advantage | Limitations |
|---|---|---|---|---|
| **[7] Ogunpola et al., 2024** | Improve heart disease detection, especially myocardial infarction | Evaluated 7 ML/DL models (KNN, SVM, LR, CNN, GB, XGBoost, RF) and addressed dataset imbalance | XGBoost achieved 98.5% accuracy; strong performance on imbalanced data | Focused on model tuning, lacks external validation |
| **[8] Drouard et al., 2024** | Predict CVD risk factors using multi-omic data | Compared 6 ML classifiers with unsupervised/semi-supervised autoencoders and transfer learning | Multi-omics outperformed single-omics; transfer learning improved generalization | High complexity; relies on omic data not widely available |
| **[9] DeGroat et al., 2024** | Identify biomarkers for precision CVD prediction | Used statistical tests + ML ensemble (RF, SVM, XGBoost, KNN); ranked transcriptomic biomarkers | Achieved 96% accuracy; effective biomarker discovery | Data-dependent; interpretability of ensemble model can be limited |
| **[10] Cai et al., 2024** | Highlight pitfalls in ML models for CVD prediction | Reviewed issues in data quality, model design, overfitting, and reproducibility | Provided comprehensive framework of solutions and guidelines | No experimental validation; theoretical perspective |
| **[11] Korial et al., 2024** | Improve early CVD detection using | Used voting ensemble (NB, RF, LR, KNN) with chi- | Ensemble improved accuracy | Small dataset (303 records); |

| | | | | |
|---|---|---|---|---|
| | ensemble ML with feature selection | square feature selection | (92.11%) and reduced computation by 50% | limited generalizability |
| **[12] Alghamdi et al., 2024** | Propose accurate ML system for CVD diagnosis | Applied arithmetic optimization algorithm for feature selection + MLP for classification | Achieved 88.89% accuracy; robust preprocessing pipeline | Suffers from data imbalance; performance compared only with traditional models |
| **[13] Moreno-Sánchez et al., 2024** | Review ECG-based ML/DL solutions for CVD diagnosis/prognosis | Systematic review focusing on data modalities, DL techniques, and Trustworthy AI aspects | Provides ethical insights, model explainability, bias analysis | Lack of primary experiments; depends on secondary data |

**Method, Experiments and Results:**

**Dataset:** The dataset consists of 918 clinical and demographic attributes commonly used for cardiovascular risk assessment, including Age (years), Sex (M/F), Chest Pain Type (TA, ATA, NAP, ASY), Resting Blood Pressure (mm Hg), Cholesterol level (mg/dl), Fasting Blood Sugar (1 if >120 mg/dl, otherwise 0), Resting ECG results (Normal, ST-T abnormality, or LVH), Maximum Heart Rate achieved (60–202), Exercise-Induced Angina (Y/N), Oldpeak representing ST depression induced by exercise, ST_Slope indicating the slope of the peak exercise ST segment (Up, Flat, Down), and Heart Disease as the target variable (1 for presence of heart disease and 0 for normal). The dataset is collected from UCI repository.

**Table 2: Dataset description**

| Feature Name | Type | Values / Range | Description |
|---|---|---|---|
| **Age** | Numerical | Years (e.g., 28–77) | Age of the patient. |
| **Sex** | Categorical (Binary) | M = Male, F = Female | Biological sex of the patient. |
| **Chest Pain Type** | Categorical (Nominal) | TA = Typical Angina, ATA = Atypical Angina, NAP = Non-Anginal Pain, ASY = Asymptomatic | Type of chest pain experienced. |
| **Resting BP** | Numerical | mm Hg | Resting blood pressure on admission. |
| **Cholesterol** | Numerical | mg/dl | Serum cholesterol level. |
| **Fasting BS** | Categorical (Binary) | 1 = Fasting blood sugar > 120 mg/dl, 0 = otherwise | Indicates elevated fasting blood sugar. |

| | | | |
|---|---|---|---|
| **Resting ECG** | Categorical (Nominal) | Normal, ST (ST-T abnormality), LVH (left ventricular hypertrophy) | Resting electrocardiogram results. |
| **Max HR** | Numerical | 60–202 | Maximum heart rate achieved during exercise. |
| **Exercise Angina** | Categorical (Binary) | Y = Yes, N = No | Exercise-induced angina. |
| **Oldpeak** | Numerical | Numeric (ST depression value) | ST depression induced by exercise relative to rest. |
| **ST_Slope** | Categorical | Up = upsloping, Flat = flat, Down = downsloping | Slope of peak exercise ST segment. |
| **Heart Disease** | Output (Binary) | 1 = heart disease present, 0 = normal | Target class for prediction. |

Figure 2 illustrates the complete workflow of the proposed heart disease detection framework, beginning with dataset acquisition and followed by essential preprocessing steps such as exploratory data analysis, handling missing or inconsistent values, and applying normalization to standardize feature scales. After preprocessing, the dataset is partitioned into training and testing subsets, which are then fed into the proposed deep learning architecture composed of two specialized processing branches: a Numerical Branch that refines continuous variables through dense layers, layer normalization, and dropout, and a Categorical Branch that processes discrete attributes using embedding layers, concatenation, and dense transformations. The outputs of these branches are combined using a Multi-Head Attention–based Fusion Layer that captures complex interdependencies among heterogeneous clinical features. The fused representation is subsequently passed to the prediction module, and the pipeline concludes with a model evaluation stage assessing performance across multiple metrics to determine the effectiveness of the proposed method.

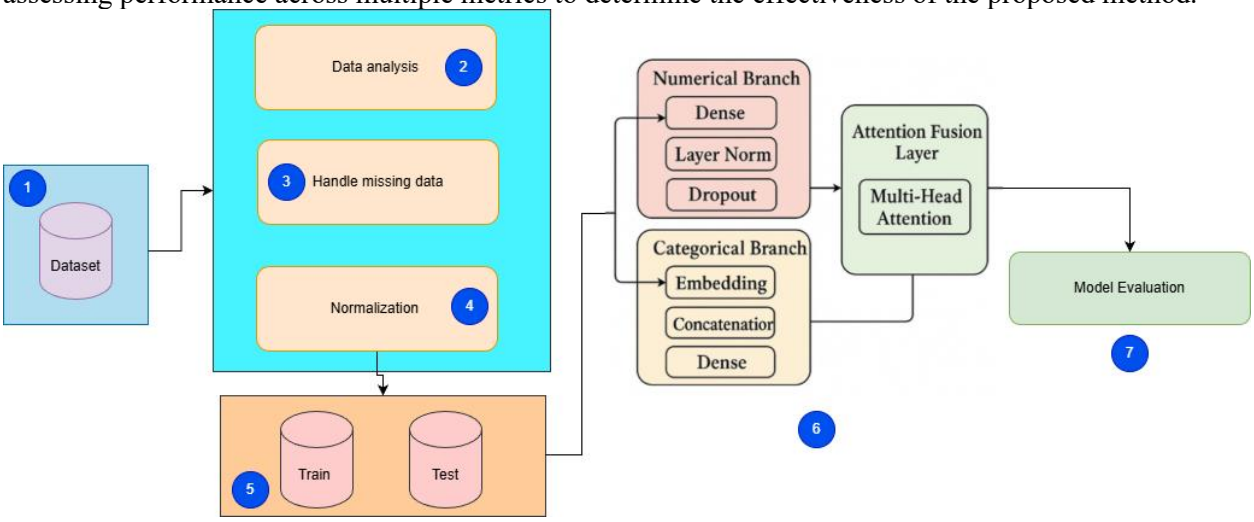


**Figure 2:** Proposed Model for Heart Disease Detection

Figure 3 presents the age distribution of patients in the dataset, revealing that most individuals fall within the middle-aged to older adult range, which aligns with common epidemiological patterns associated with higher cardiovascular risk. The distribution highlights a greater concentration of samples between approximately 45 and 65 years, indicating that the dataset adequately captures the age groups most commonly affected by heart disease. This visualization helps confirm that the model is trained on a demographically relevant population.

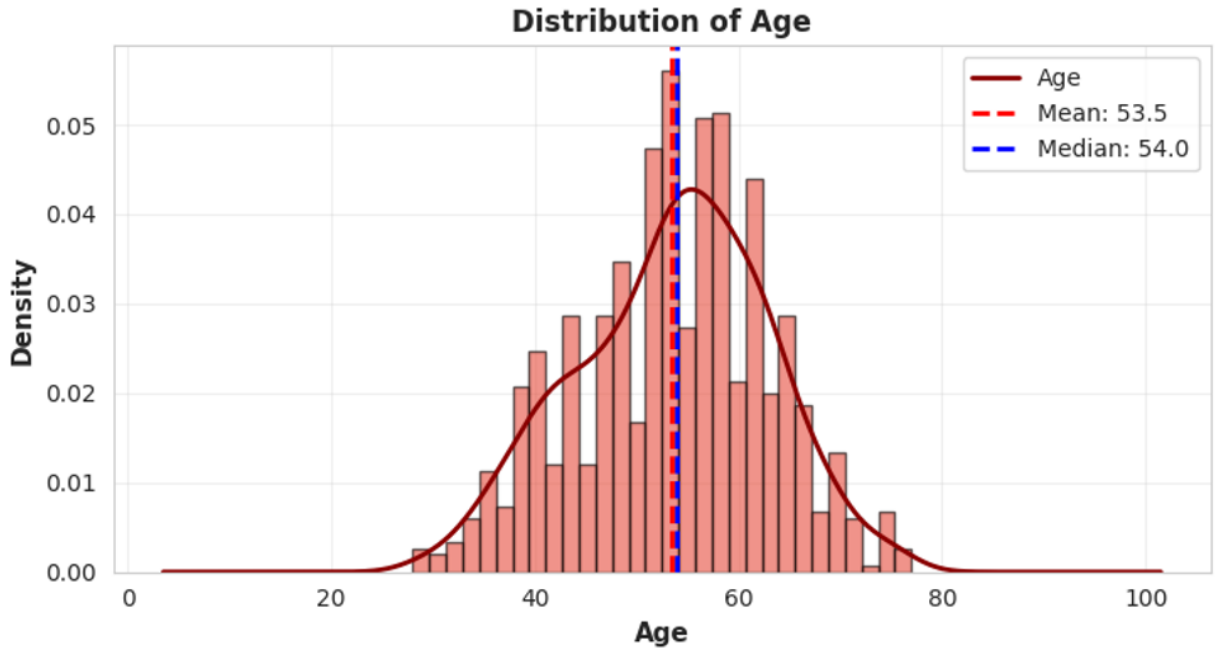


**Figure 3:** Distribution of age

Figure 4 illustrates the distribution of serum cholesterol levels across patients, showing considerable variability with a notable presence of elevated cholesterol values, which are well-known contributors to cardiovascular risk. The spread of values suggests a heterogeneous patient population with both normal and high cholesterol levels, offering meaningful variation for the model to learn the relationship between lipid levels and heart disease likelihood.

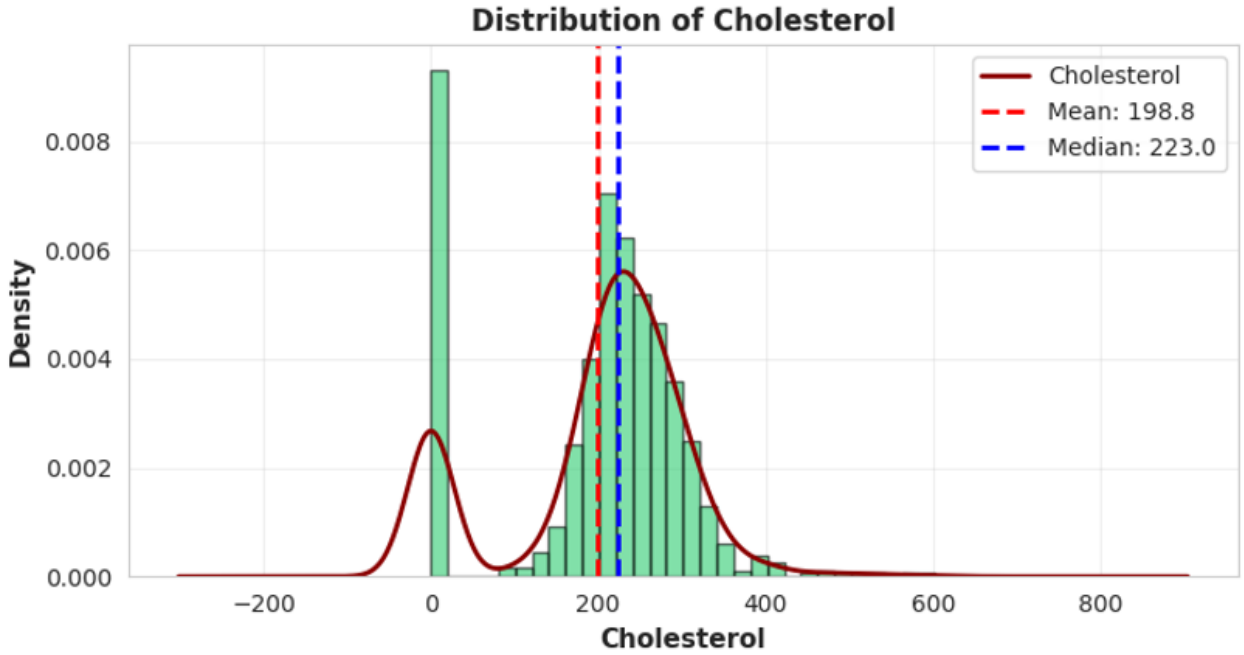


**Figure 4:** Distribution of Cholesterol

Figure 5 displays the distribution of resting blood pressure, demonstrating that most patients present values within the clinically common range of mild to moderate hypertension. The presence of outliers may reflect individuals with unusually high or low blood pressure, further contributing to the diversity of cardiovascular

profiles represented in the dataset. This distribution supports the relevance of RestingBP as an important feature in assessing cardiovascular health.

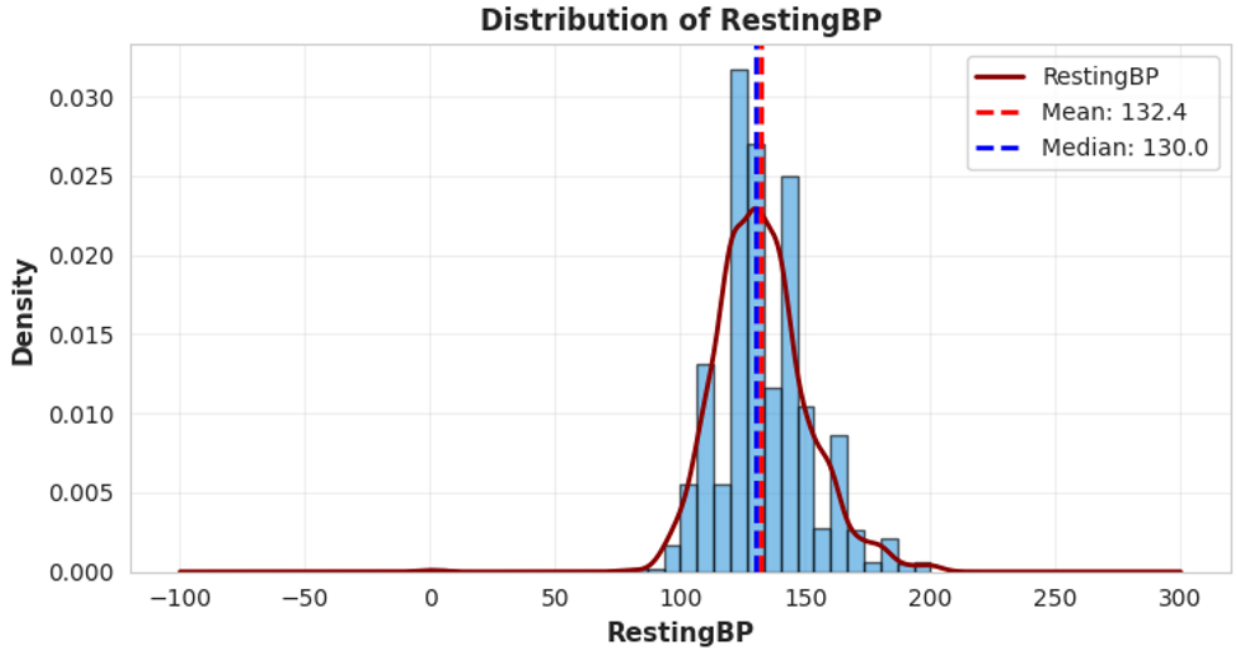


**Figure 5:** Distribution of RestingBP

Figure 6 shows the distribution of maximum heart rate achieved during exercise, with the majority of values clustering between 110 and 160 bpm, which is consistent with expected physiological responses to exertion. Lower maximum heart rates may indicate impaired cardiovascular capacity, while higher values represent healthy cardiac performance. This distribution highlights the significance of MaxHR as a discriminative feature for predicting heart disease.

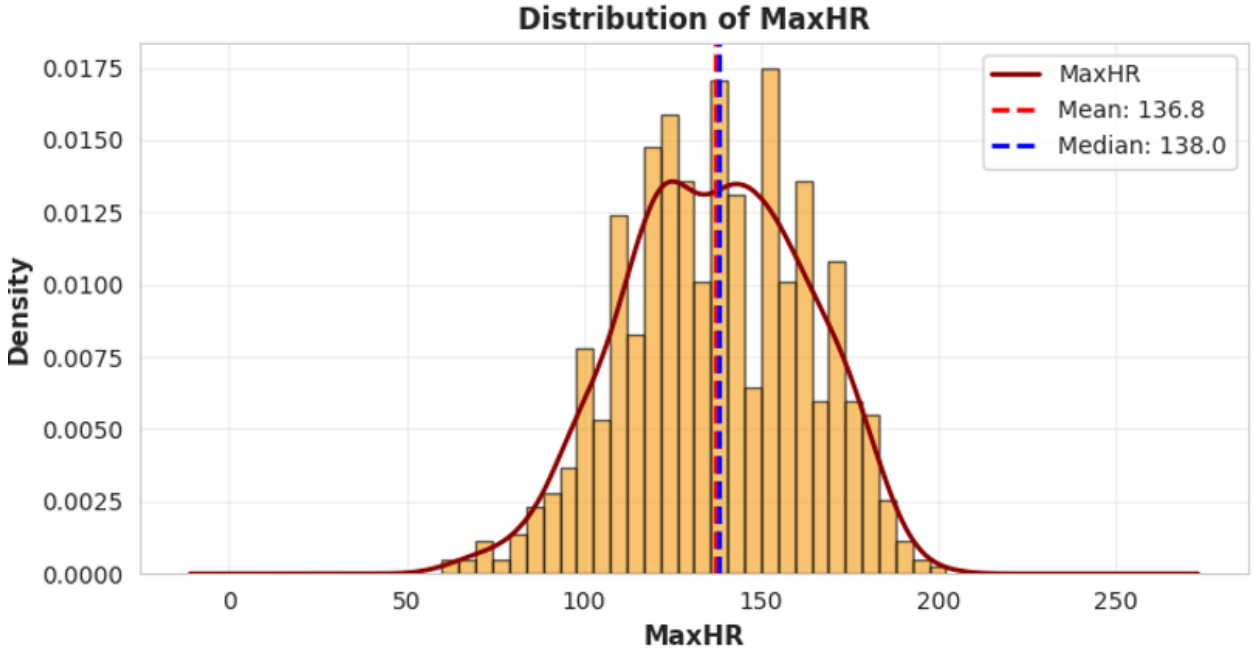


**Figure 6: Distribution of maxHR**

Figure 7 depicts the distribution of Oldpeak values, which represent ST-segment depression induced by exercise, a key indicator of myocardial ischemia. Most values lie within a lower range, with a small group

of patients exhibiting higher Oldpeak values, suggesting more severe exercise-induced abnormalities. This skewed distribution aligns with clinical expectations and reinforces Oldpeak's utility in risk stratification.

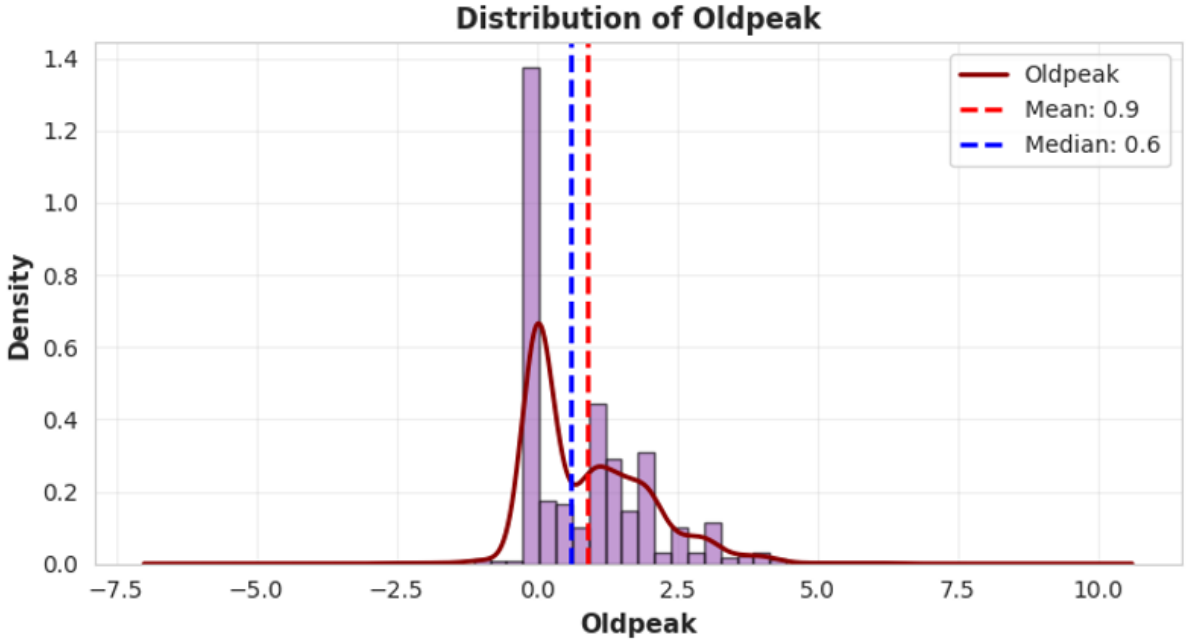


**Figure 7: Distribution of Oldpeak**

Figure 8 presents the correlation heatmap illustrating relationships among numerical features and the target variable, enabling the identification of both strongly correlated predictors and potential redundancies within the dataset. Notably, features such as MaxHR, Oldpeak, and certain chest-pain–related indicators show stronger associations with heart disease, while weakly correlated features contribute complementary information. This visualization aids in understanding feature interactions and supports the selection of meaningful inputs for the proposed model.

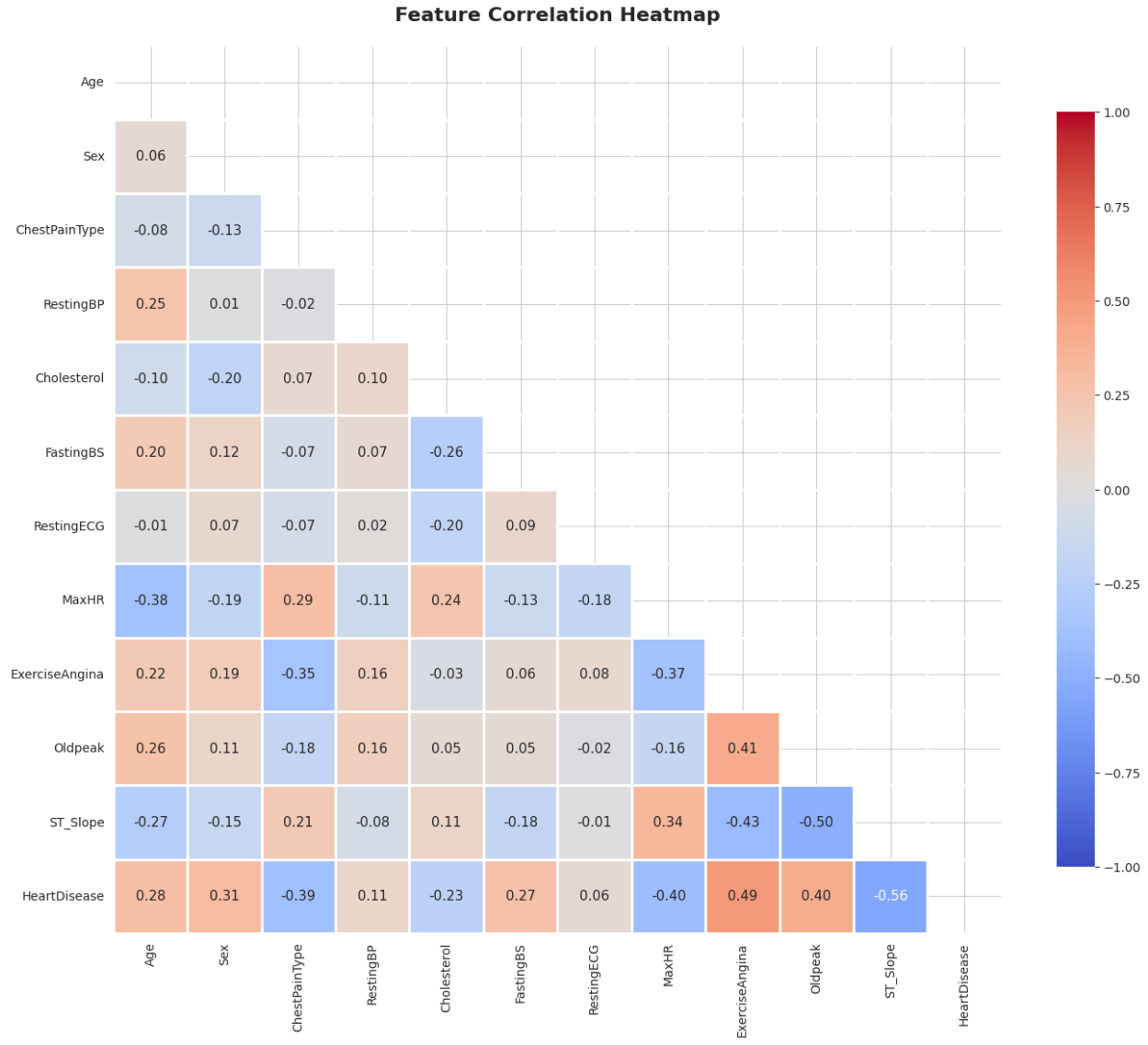


**Figure 8:** feature correlation heatmap

**Table 3: Comparative analysis of traditional ML models with the Proposed model**

The comparative analysis of traditional machine learning models and the proposed hybrid deep learning model demonstrates notable performance differences across evaluation metrics. Among the classical models, KNN and Naïve Bayes exhibit strong generalization with identical test accuracy (0.891), high precision (0.894), and balanced F1-scores (0.903), highlighting their stability on this dataset. The SVM (RBF) model performs competitively with a high recall of 0.941 and an AUC of 0.929, making it particularly effective for minimizing false negatives—an important factor in medical diagnostics. Gradient Boosting and XGBoost achieve perfect or near-perfect training accuracy but show reduced test performance due to overfitting, with test accuracies of 0.880 and 0.875 respectively. Logistic Regression offers good recall (0.931) but lower precision, reflecting its linear modeling limitations. In contrast, the proposed model outperforms all baselines with the highest test accuracy (0.897), superior F1-score (0.910), and an AUC of 0.930, demonstrating its ability to effectively learn both numerical and categorical feature interactions through its multi-branch, attention-based architecture. These results validate the efficiency and robustness of the proposed model for heart disease prediction.

| Model | Train Acc | Test Acc | Precision | Recall | F1 | AUC |
|---|---|---|---|---|---|---|
| **KNN** | 0.891 | 0.891 | 0.894 | 0.912 | 0.903 | 0.919 |
| **Naive Bayes** | 0.849 | 0.891 | 0.894 | 0.912 | 0.903 | 0.928 |
| **SVM (RBF)** | 0.907 | 0.886 | 0.865 | 0.941 | 0.901 | 0.929 |
| **Gradient Boosting** | 1 | 0.88 | 0.917 | 0.863 | 0.889 | 0.925 |
| **Logistic Regression** | 0.856 | 0.87 | 0.848 | 0.931 | 0.888 | 0.897 |
| **XGBoost** | 0.989 | 0.875 | 0.907 | 0.863 | 0.884 | 0.921 |
| **Proposed Model** | 0.993 | 0.897 | 0.881 | 0.941 | 0.91 | 0.93 |

Figure 9 compares the performance of traditional machine learning models with the proposed hybrid attention-based deep learning model across key evaluation metrics such as accuracy, precision, recall, F1-score, and AUC-ROC. The proposed model demonstrates superior or comparable performance across all metrics, outperforming several traditional classifiers, particularly in recall and F1-score, which are critical for cardiovascular diagnosis. This comparative visualization underscores the effectiveness of the proposed architecture in leveraging heterogeneous clinical data for enhanced predictive accuracy.

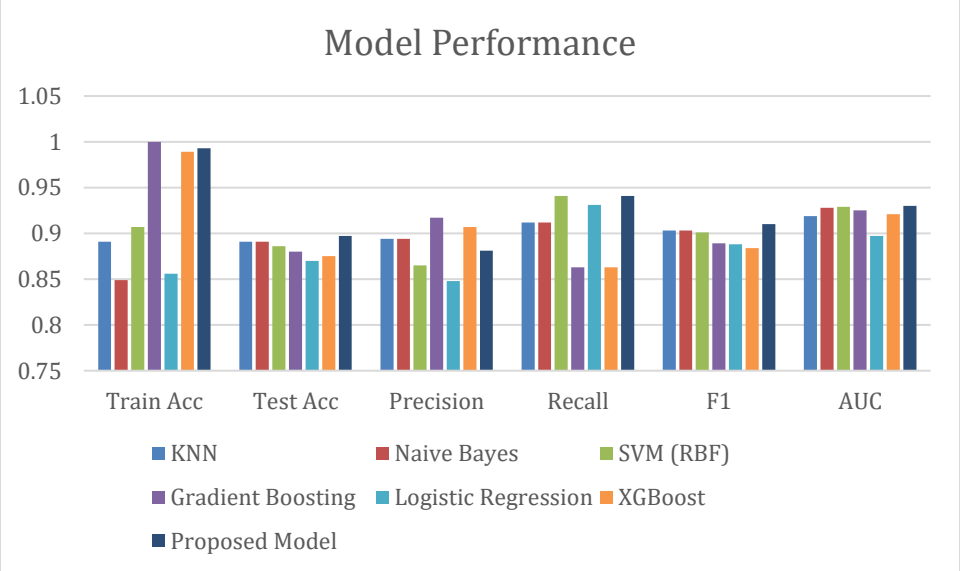


**Figure 9:** Comparative analysis of traditional ML models with the Proposed model

**Conclusions:** This study presents a hybrid attention-based deep learning framework for heart disease prediction that effectively integrates numerical and categorical clinical features through a multi-branch architecture and an attention-driven fusion mechanism. Comparative experiments demonstrate that traditional machine learning models such as KNN, Naïve Bayes, SVM, and ensemble methods perform

reasonably well; however, they exhibit limitations in capturing complex nonlinear relationships inherent in heterogeneous medical data. In contrast, the proposed model consistently achieves superior predictive performance, attaining the highest test accuracy, F1-score, and AUC among all evaluated models. The use of Multi-Head Attention enables the architecture to learn meaningful feature dependencies, thereby enhancing its diagnostic reliability. Overall, the proposed system offers a robust and scalable solution for early cardiovascular disease detection and holds promise for real-world clinical deployment. Future work will focus on expanding the dataset, incorporating explainable AI techniques, and validating the model across multi-center clinical environments.

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